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BANK SYSTEMIC RISK-TAKING AND LOAN PRICING: EVIDENCE FROM SYNDICATED LOANS

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Bank Systemic Risk-Taking and Loan Pricing: Evidence from Syndicated Loans

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Abstract

In this paper we document evidence of systemic risk taking from syndicated loan pricing. Using U.S. syndicated loan data, we find that the borrower's idiosyncratic risk is positively priced whereas systematic risk is negatively related to loan spreads, controlling for firm, loan and bank specific variables. We argue that the underpricing of systematic risk relative to idiosyncratic risk suggests banks' preference for investing in systematic risk which increases interbank correlation and systemic risk of banks. We relate the incentive for systemic risk-taking to the "too-many-to-fail" guarantee. We further show that small and lowly correlated banks underprice systematic risk relative to big and more correlated banks.

JEL classification: G21, G32

Keywords: Systemic risk-taking; Loan pricing; Public guarantees; Too-many-to-fail; Syndicated Loans

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1 Introduction

There has been a burgeoning literature that tries to identify and explain bank risk-taking (Laeven and Levine, 2009; Keeley, 1990; Gropp, Gruendl and Guettler, 2013; Gropp, Hakenes and Schnabel, 2010; Deyoung, Peng and Yan, 2013; Altunbas, Gambacorta and Marqués-Ibáñez, 2010). However, little empirical work has been done to examine bank systemic risk-taking, even though the theoretical importance has been widely recognized. In this paper we attempt to identify bank systemic risk-taking from mispricing (or underpricing) of aggregate risk in the syndicated loans and to further relate the systemic risk-taking incentive to "too-many-to-fail" guarantee, using a sample of the U.S. syndicated loan data over the period 1988 to 2011.

We begin by documenting the evidence of bank systemic risk-taking in the syndicated loan markets from loan pricing. As a debt contract, a syndicated loan is priced to reflect its underlying credit risk, which can be decomposed into aggregate (or systematic) and idiosyncratic risks. A bank can increase its systemic risk by betting on aggregate exposures of loans. In principle, aggregate risk which cannot be diversified away is expected to be priced relative to diversifiable idiosyncratic risk. However, the underpricing of aggregate risk relative to idiosyncratic risk can be interpreted as evidence of banks undertaking excessive (incorrectly priced) systemic risk. In this study we use systematic and idiosyncratic equity volatilities of the borrower as proxies for the aggregate and idiosyncratic credit risks of the loan contract. We show that loan spreads are positively related to borrowers' idiosyncratic risk whereas negatively related to aggregate risk, controlling for borrower, loan and lender specific factors, and year dummies. The mispricing of aggregate risk can be taken as evidence of bank taking systemic risk. This pricing pattern is robust to risk measures of equity volatility from CAPM regression and Fama-French three factor regression. In addition, we show that such pricing pattern is not driven by borrowers' or lenders' unobserved heterogeneity as our results continue to hold when including firm fixed effects and bank fixed effects.

The underpricing of aggregate risk suggests that the systemic risk-taking behavior cannot be explained by the "search for yield" hypothesis that banks invest in systematically risky loans to earn high risk premium. By contrast, we show that the underpricing of aggregate risk is consistent with the prediction of the regulatory arbitrage hypothesis that banks may exploit the benefits of public guarantees. In particular, banks protected by the public guarantee expect to be bail out in systemic crisis and therefore are less concerned with aggregate risk. By contrast, nonbank lenders which have no bailout expectation should correctly price aggregate risk ex ante. Therefore, we test the impact of the presence of public guarantee on loan pricing. The regression results show no evidence of systemic risk-taking by nonbank lenders as the aggregate risk is pronouncedly priced relative to idiosyncratic risk in the cohort of loans originated by nonbank lenders which are not protected by the government guarantees as commercial banks are. The sharp discrepancy in pricing patterns between banks and nonbank lenders reveals the impacts on the presence of government guarantees on systemic risk-taking.

We show that our results are not driven by "too-big-to-fail" guarantee, but rather are explainable by the "too-many-too-fail" guarantee. According to the "too-big-to-fail" story, big banks are expected to take more risk as protected by the "too-big-to-fail" guarantee in crisis. When interacting borrower's aggregate and idiosyncratic risks with bank size dummy, however, we find small banks charge lower spreads on aggregate risk relative to big banks. When splitting the sample into small bank group and big bank group, we find only small banks underprice aggregate risk. By contrast, small banks have stronger incentives to take systemic risk as the bailout subsidy increases for small banks when big banks also fail but it does not increase for big banks when small banks fail as big banks can acquire failed small banks. The increment of systemic importance by taking systemic risk can raise the likelihood of failing together, and therefore is especially valuable for small banks. To corroborate the argument that systemic risk-taking is driven by the "too-many-to-fail" guarantee, we further interact interbank correlation dummy with borrower's aggregate and idiosyncratic risks. The results suggest that lowly correlated banks charge lower spreads on aggregate risk relative to highly correlated banks, consistent with the "too-many-to-fail" story that lowly correlated banks are inclined to increase the likelihood of collective bailout by taking systemic risk.

On top of the evidence from loan pricing, we provide evidence of "too-many-to-fail" guarantee driven systemic risk-taking from lending amounts. We show that lowly correlated banks tend to lend more to systematically risky borrowers in both relative facility shares and absolute loan amounts.

This paper makes two contributions to the literature. First, in spite of fruitful studies on bank risk-taking in general, the specific research on bank systemic risk-taking has been restrained to theoretical models as it is challenging to identify systemic risk taking behavior in real world. Our paper adds new empirical evidence of bank systemic risk-taking from the syndicated loan market. Unlike Cai, Saunders and Steffen (2011) which also document bank systemic risk-taking based bank interconnectedness constructed from syndicated loan portfolios, we illustrate systemic risk taking from mispricing of aggregate risk of loans. The method of identifying risk-taking from mispricing of risk has also been applied in Ioannidou, Ongena and Peydro (2008) and Paligorova and Santos(2012).

Second, "too-many-to-fail" problem has become a popular agenda in bank regulation especially since the recent financial crisis (see Dam and Koetter, 2012; Vives, 2011). However, scarce empirical work has been done in testing this theory. The only exception is Brown and Dinc (2009) which documents evidence of the "too-many-to-fail" effect that regulators are ex post reluctant to close failed banks when other banks in the country are also weak. Our paper is the first work that unveils evidence that banks ex ante have incentives to take exposures to systematic risk factors in expectation of the "too-many-to-fail" guarantee. Broadly speaking, our work also contributes to the empirical study of public guarantees on bank risk-taking by providing evidence that public guarantees encourage protected banks risk-taking. This finding is similar to the moral hazard effect of deposit insurance in the literature (Merton, 1977).

One caveat of our research is that we document systemic risk-taking from syndicated loans, which is only one asset category of banks. Other assets types such as mortgage lending and mortgage back securities (MBS) are also shown to be important vehicles for bank herding and systemic risk-taking (Ma, 2014).

The remainder of the paper is organized as follows. Section 2 presents our data, methodology and summary statistics. Section 3 examines bank systemic risk-taking from loan pricing. Section 4 analyzes the incentive for systemic risk-taking and highlights the importance of public guarantees. Section 5 first rejects the role of "too-big-to-fail" guarantee in bank systemic risk-taking and then shows the effect of the "too-many-to-fail" guarantee. Section 6 shows banks not only underprice aggregate risk but also lend more to systematically risky borrowers. In the end, we conclude in section 7.

2 Data, Methodology and Summary Statistics

2.1 Data

Obtaining syndicated loan data from LPC Dealscan, we focus on U.S. firms borrowing from U.S. banks over the period between 1988 and 2011[1]. We exclude loans borrowed by companies in the financial sector from our sample (SIC codes 6000 to 6400, Finance and Insurance). Our analysis focuses on lead arrangers, which are delegated to collect information and monitor the borrower on behalf of the syndicate and set loan terms and pricing[2]. Syndicated loans are usually structured in a number of facilities, also called tranches. We treat facilities in each deal as different loans because spreads, identity of lenders and other contractual features often vary within a syndicated loan deal. This is a common practice in loan pricing literature (See similar analyses in Carey and Nini, 2007; Focarelli, Pozzolo and Casolaro, 2008; Santos, 2011). Therefore, each observation in our regressions corresponds to a syndicated loan facility. Our results are qualitatively unchanged when using loan characteristics of the largest tranche for loans of multiple tranches or analysis at the deal level.

By merging Dealscan with Compustat, we have detailed annual accounting information of borrowers[3]. Compustat consists of annual report data of publicly listed American companies, which are assumed to have less information problems than privately held firms.

To calculate equity volatility of borrowers, we collect daily stock return data over the year leading up to the facility activation date from CRSP for borrowers listed in NYSE, AMEX and NASDAQ[4]. We drop out borrowers with less than 100 trading days available in the event window[5]. Moreover, we collect Fama-French Factors from Wharton Research Data Services (WRDS).

In the end, we focus on loans with single lead arranger so that we can clearly identify the

[1]Before 1987, the coverage of Deanscan is uneven.

[2]Dealscan indicates the role of each lender. We follow the classification rule in Cai, Saunders and Steffen (2011). If the variable *LeadArrangerCredit* indicates “Yes”, a lender is classified as a lead arranger. We correct for the role of lenders of loans that *LeadArrangerCredit* indicates “Yes” but “LenderRole” falls into participant as non-lead arranger. In addition, if no lead arranger is identified, we treat a lender as a lead arranger if its “LenderRole” is classified as following items: Admin agent, Agent, Arranger, Bookrunner, Coordinating arranger, Lead arranger, Lead bank, Lead manager, Mandated arranger, Mandated Lead arranger.

[3]We are indebted to Sudheer Chava and Michael Roberts for providing the link between Dealscan with Compustat, see Chava and Roberts (2008).

[4]We link LPC Deanscan with Compustat via GVKEY. Next, we use PERMNO to link Compustat with CRSP.

[5]Campbell and Taksler (2003) argue that a fairly long event window is required to measure the volatility that is publicly observed by corporate bond investors.

impact of lender characteristics on loan pricing[6]. We manually match lead banks in Dealscan with commercial banks in Call reports, depending on bank names, geographical locations and operating dates. We complement the unmatched sample with banking holding companies from Federal Reserve Y-9C reports. Additionally, we control for mergers and acquisition by matching the lender to the accounting information of the acquirer.

To calculate the market based interbank correlation, we collect banks' daily stock return data one year preceding to the quarter of loan origination from CRSP. The S&P 500 banking sector index comes from Datastream tracing back to the last quarter of 1989. We link bank stock return with Call Reports and FY Y9C using the CRSP-FRB link from Federal Reserve Bank of New York. In particular, we match commercial banks that are subsidiaries of listed bank holding companies with the stock information of their parent companies.

2.2 Loan pricing model

In a typical loan syndication process, a lead arranger offers a lending rate and negotiates with the borrower on behalf of the syndicate. In principle, the lead arranger takes into account both idiosyncratic and aggregate risks of the borrower to evaluate the her capacity of repayment. According to the standard asset pricing literature, aggregate risk should be priced relative to idiosyncratic risk. The incorrectly pricing of aggregate risk, that is, aggregate risk is priced lower than idiosyncratic risk, indicates lenders take excessive aggregate risk. The increment in aggregate exposures can raise bank systemic risk. Overall, we examine systemic risk-taking from the relative pricing of aggregate risk to idiosyncratic risk. In addition, the lead arranger also assesses borrowers other characteristics, lenders characteristics, non-price loan contract terms and macroeconomic conditions. Therefore, we control for all these information in our baseline loan pricing model as follows:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 SysVol_{i,t-1} \\ &+ \sum_j \gamma_j Firm_{i,t-1} + \sum_k \theta_k Loan_{f,t} + \sum_n \psi_n Bank_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t} \end{aligned} \tag{1}$$

[6]It makes less sense if we aggregate lenders' characteristics for loans with multiple lead arrangers. Nevertheless, our results that banks underprice systematic risk relative to idiosyncratic risk hold for loans granted by multiple lead arrangers.

where f, i, b and t denote facility, firm, bank and year, respectively. The dependent variable, *LoanSpread*, is all-in-drawn spread in Dealscan which denotes an interest spread over Libor measured in basis points. *IdioVol* and *SysVol* represent idiosyncratic and aggregate risks, respectively. We include firm specific variables ($Firm_i$), loan specific variables ($Loan_f$) and bank specific variables ($Bank_b$). We also include year dummies T throughout all specifications. ϵ is the error term.

Estimating the baseline loan pricing model, we run cross-sectional OLS regressions that pool together all valid observations. The following loan pricing models are estimated with robust standard errors which are clustered at the borrower level to correct for correlation across observations of a given firm, though our results are insensitive to clustering at lender or borrower-lender pair levels.

To compute our key independent variables, idiosyncratic and aggregate risks of the borrower, we rely on the borrower's equity volatilities which are forward-looking and driven by market information. The idea is that we can think of the holder of risky debt as the owner of riskless bonds who have issued put options to the holder of firm equity (Merton, 1974). The strike price equals the face value of the debt and reflects limited liability of equity holders in the event of default. Increased equity volatility raises the value of put option, benefiting the equity holder at the expense of the debt holder. Hence a firm with more volatile equity is more likely to reach the bound condition for default. In addition, there is a burgeoning literature that applies equity volatility to explain credit spreads. In a seminal paper Campbell and Taksler (2003) find evidence that equity volatility, especially idiosyncratic equity volatility, has substantial explanatory power for corporate bond yields. Zhang, Zhou and Zhu (2009) and Ericsson, Jacob and Oviedo (2009) apply the same logic to credit default swap (CDS) pricing and find equity volatility is an important determinant of CDS spreads. Gaul and Yusal (2013) also relate equity volatility with loan spreads to explain the "global loan pricing puzzle" in Carey and Nini (2007). Acharya, Almeida and Campello (2013) use equity beta to explain the cost of credit lines.

We further decompose borrowers' equity volatility into idiosyncratic and systematic components to proxy idiosyncratic and aggregate risks, respectively. We run a standard CAPM regression as follows:

$$r_{i,t} - r_t^{free} = \beta_{i,t}^{CAPM} \times (r_t^m - r_t^{free}) + \epsilon_{i,t} \tag{2}$$

where r_i, r_t^m and r_t^{free} are individual stock daily return, market return calculated as the value-weight return on all NYSE, AMEX, and NASDAQ stocks in CRSP and risk free return proxied by the one-month Treasury bill rate, respectively. We define the idiosyncratic volatility as standard deviation of the residual, $IdioVol^{CAPM}$=$SD(\epsilon)$. In addition, we define the aggregate risk as the product of beta and market volatility, $SysVol^{CAPM}$=$\beta^{CAPM} \times MarketVol$, where $MarketVol$ is the standard deviation of market excess return, $MarketVol$ =$SD(r^m - r^{free})$.

Alternatively, we adopt Fama French (1993) three-factor model using the following regression:

$$r_{i,t} - r_t^{free} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{SMB} \times SMB_t + \beta_{i,t}^{HML} \times HML_t + \varepsilon_{i,t} \tag{3}$$

Where the market factor MKT_t is the value-weight return on all NYSE, AMEX, and NASDAQ stocks from CRSP minus the one-month Treasury bill rate, the size factor SMB_t is the average return on the three small portfolios minus the average return on the three big portfolios, the value factor HML_t is the average return on the two value portfolios minus the average return on the two growth portfolios, respectively. We stick to the standard deviation of the residual $IdioVol^{FF} = SD(\varepsilon)$ as idiosyncratic volatility. On the other hand, we follow Balin, Brown and Caglayan (2012) and define the aggregate risk in the multifactor model as the total volatility that is attributable to Fama French factors and the factors' cross-covariances, $SysVol^{FF} = \sqrt{TotalVol^2 - IdioVol^{FF^2}}$. In the end, we annualize all equity volatilities by a multiplier of $\sqrt{252}$ as we use daily stock returns.

We include a number of firm level controls that may affect the lending interest rates. *Sales* is the log of the firm's sales at close in millions of dollars. Larger firms are more informationally transparent, therefore we expect larger borrowers have lower spreads. Next, *Leverage* is a ratio of total debts to total assets. Highly leveraged firms are more likely to default, hence we expect they are charged a higher lending rate. In addition, we use *Z score* to control for the borrowers' likelihood of bankruptcy. As a higher Z score indicates lower credit risk, we expect firms with higher Z scores to obtain lower loan spreads. Besides, we control for *Profit Margin*, which measure the performance and profitability of the borrower. As a profitable firm is safe and less likely to fall into financial distress, it should be charged a low spread. As for the firm specific controls that affect loss given default (LGD), we include new working capital and tangibles assets. *NWC* measures a ratio of net working capital to total assets. We expect firms with more net working capital to lose less value in the event of default. In addition, *Tangibles* measures a fraction of tangible assets to total assets. Borrowers with a higher fraction of tangible assets are more informationally transparent (Morgan, 2001) and have higher values in the event of default as the value of intangible assets are much volatile. Therefore we expect a lower spread on the loans granted to borrowers with a higher fraction of tangible assets. We control for Market-to-Book ratio *MKTBOOK*, an imperfect proxy of Tobin's q, which is a ratio of the market value of a firm to its accounting value. We expect a firm with a higher Market-to-Book ratio to have lower spreads[7].

Even though loan specific variables are jointly determined with loan spreads and therefore are endogenous, we include these contractual features. We include *Facility Size*, measured by the log of the tranche amount in millions of dollars. Large loans are likely to be associated with greater credit risk in the underlying project and lower liquidity, but could also be related to larger borrowers which have more cushions against adverse shocks. Therefore, the impact of *Facility Size* on loan pricing is not unambiguous. Additionally, we include *Maturity* which is the maturity of the facility in months. The effect of maturity on loan spreads is also ambiguous. Next, we use *Number of Lenders* within a facility and *Number of Facilities* within a deal to proxy the syndicated structure. To proxy for the liquidity exposure of each facility, we classify a loan as a line of credit (*Revolver*) or a term loan (*Term Loan*)[8]. Moreover, we include dummy variables that indicate whether a loan is senior (*Senior*) in the borrowers' liability structure and whether the loan is secured by collateral (*Secured*). Seniority and collateral may reduce the lenders' loss in the event of default and therefore reduce lending rate, however,

[7]In the previous version, we include industry dummies that classify borrowers into ten sectors based on 2-digit SIC codes. We expect the industry dummies to capture industrywide risks that borrowers are facing but not captured by the aforementioned firm controls. However, we exclude industry dummies for fear of multicollinearity.

[8]In particular, a loan is classified as a revolver is the loan type is expressed in Dealscan as "364-Day Facility", "Revolver/Line < 1 Yr.", "Revolver/Line >= 1 Yr.", "Revolver/Term Loan", "Demand Loan", "Limited Line". Alternatively, a loan is defined as a term loan if the loan type is recorded as "Term Loan", "Term Loan A", "Term Loan B", "Term Loan C", "Term Loan F", "Delay Draw Term Loan".

the contractual arrangement may be ex ante required to protect lenders towards specifically risky borrowers. Therefore, the relation between seniority, collateral and loan pricing is an empirical question. Last, we control for loan purpose dummies into five categories: Corporate Purpose, Debt Repayment, Takeover, Working Capital and Other.

As the loan contract is negotiated between the borrower and lenders, we believe that lenders' characteristics may have impacts on loan pricing. Santos and Winton (2009) analyze how bank capital, borrower cash flow and their interaction affect loan pricing. They show that less capitalized banks charge relatively more for borrowers with low cash flow but offer discounts for borrowers with high cash flow. Santos (2010) emphasizes the impacts of bank losses on loan contracts. He shows evidence of credit crunch in the subprime crisis that even though firms paid higher loan spreads and took out smaller loans during the subprime crisis, the increase in loan spreads was higher for firms that borrowed from banks that incurred large losses. In particular, as lead arrangers coordinate the syndication with participants as well as the negotiation with the borrower, we focus on lead arrangers' characteristics. First, we include *Size BK* as the log of bank total assets in millions of dollars. Large banks usually have diversified portfolios and good risk management, therefore we expect large banks charge low lending rates. Next, we control for *Capital BK*, denoted as a ratio of bank capital to total assets. Well capitalized banks have more capital buffer and therefore are expected to charge a lower spread. In addition, we use *NPL BK*, a ratio of nonperforming loans to total assets, as a measure of bank credit risk. Risky banks may charge additional compensation for undertaking extra risk. Hence, we expect banks with a higher proportion of nonperforming loans to charge a higher spread. We also use *Z Score BK* as a direct measure of bank risk. We calculate Z score following Laeven and Levine (2009) but use an eight-quarter rolling window. Moreover, we include a bank profitability measure *ROA BK*. More profitable banks are expected to charge a lower rate. To control for the impact of bank liquidity on loan rates, we include *Liquidity BK* to measure the liquidity of bank assets, which a ratio of liquid securities and cash to total assets. Besides, we include the growth rate of loans (*Loan Growth BK*) to measure investment opportunities of the lender. In the end we use *Cost of Funds BK* which is total interest expenses over total liabilities to measure funding costs.

In particular, we use the accounting information of the borrower and lenders from the fiscal year ending in the calendar year $t-1$ for loans made in calendar year t. To eliminate the bias from outliers, we winsorize loan spreads, firm and bank specific variables and borrowers' equity volatilities at 1 and 99 percentile levels[9]. We include year dummies to capture time trends throughout the analysis as Santos (2011) has shown the business cycle effect on loan contracts.

2.3 Summary Statistics

Our final sample consists of 469 U.S. banks granting 11 278 facilities to 4 183 U.S. firms. Table 1 presents summary statistics of our sample before winsorizing. The average loan spread is 208 basis points over Libor. The average CAPM Idiosyncratic Volatility is 0.56, very close to the mean of total volatility. Since market is usually relatively stable, the average Systematic Volatility which is the product of Beta and Market Volatility is rather small (0.12), much smaller than the average beta (0.76). It is worth noting that systematic volatility could be negative as the beta of some borrowers is negative. The idiosyncratic and systematic volatilities estimated from CAPM and Fama French three factor models are quite similar.

Looking at firm level controls, we find the average log of firm total assets is 5.6. It is worth noting that the log of facility size can be negative when the loan is pretty small. The mean of borrowers' leverage is 28 percent. On average, the Z score of firms are 4 in our study. The profit margin is highly skewed, with a mean of -20.75 percent and a median of 3.19 percent. The mean of net working capital to total assets and tangible assets to total assets are 21 and 69 percent, respectively. The average market to book ratio is 1.82.

We turn to the loan controls in our sample. The average log of facility amount is 3.79. The information of the retained share of lead arrangers is available for a small proportion of around 5700 facilities only. On average, a lead arranger retains a share of 56 percent of the facility. On the other hand, the absolute amount of the lead arranger's stake is 2.64 when we look at the log of facility amount. Syndicated loans in our sample have an average maturity of 43 months. In addition, on average each syndicate has 6 lenders and is structured into 1.77 facilities. Looking at the loan types, 73 percent of loans are lines of credit while 24 percent are term loans. Almost all loans are senior in the borrower's liability structure. In the end, 75 percent of loans are secured by collateral.

We check the sample characteristics of banks. Banks are much larger as the average log

[9] See Table 8 to 10 for detailed information of variables.

of bank total assets is 18.15. The average equity to asset ratio is 7.56 percent. The average share of nonperforming loans to gross loans is less than 1 percent. The mean of bank Z score is 3.17. The average ROA is also below 1 percent. Liquid assets account for 18.77 percent of total assets. The average loan growth rate is rather high at 22 percent. The average bank has the cost of funds at 3.42 percent. As not all banks are listed and traded in stock exchanges, we have the information of interbank correlation for approximately 9200 facilities. The average interbank correlation is 0.73.

3 Evidence of bank systemic risk-taking from idiosyncratic and aggregate risks pricing

In this section, we apply the baseline loan pricing model to examine bank systemic risk-taking. Table 2 reports the results of how the U.S. banks price idiosyncratic and aggregate risks of the U.S. borrowers. We estimate all specifications with robust standard errors clustered at the firm level. We present the results using idiosyncratic volatility and systematic volatility estimated from the CAPM regression in column 1. The coefficient of the idiosyncratic volatility is positive and significant, indicating banks charge risk premium for bearing idiosyncratic default of the borrower. On the contrary, the coefficient of aggregate risk is negative and significant, suggesting that banks underprice aggregate risk. Overall, we find aggregate risk is underpriced relative to idiosyncratic risk, consistent with bank systemic risk taking. We have similar results in column 2 in which we use idiosyncratic and systematic volatility estimated from the Fama French three factor model[10]. In column 3, we include total volatility as the measure of credit risk and systematic volatility as the measure of correlation as key variables of interest. We find a positive and significant coefficient for total volatility which directly suggests banks dislike credit risk and therefore charge risk premiums. Again, we find negative and significant coefficient for aggregate risk, indicating that banks underprice aggregate risk.

In addition, the firm characteristics have expected signs and are mostly significant. In particular, we find that larger firms, firms with higher profit margins, higher net working capital and tangible assets and higher market to book ratio pay lower loan spreads, whereas higher leveraged firms are charged higher lending rates. Besides, regarding to the loan specific

[10]in unreported results, even though equity beta is not comparable to volatility, we use CAPM beta and market beta in the Fama French three-factor model as measures of aggregate exposure as robustness. We find similar evidence that banks underprice aggregate risk relative to idiosyncratic risk.

variables, we find that larger loans with longer maturity, more lenders in the syndicate are related to lower spreads, while loans with more facilities are charged at a higher rate. Moreover, lines of credit are generally cheaper. A loan is much cheaper if it is senior as it ensures the priority of lender to claim to the residual value in the event of borrower bankruptcy. Furthermore, a secured loan is charged a higher spread than a similar one without collateral probably because only risky borrowers are required for collateral and are ex ante charged a risk premium. Last, we find that larger banks, well-capitalized banks, banks with high cost of funding and high loan growth rates charge lower spreads while risky banks charge relatively higher spreads. To save space, we do not report the estimated coefficient of firm, loan and bank specific control variables in the following specifications.

Our baseline specification may be prone to omitted variable bias if unobserved firm characteristics drive both firm's equity volatility and loan spreads. We restructure our data into panel data in which we have i=firm as the cross section dimension and f=facility as the time dimension. We estimate the firm fixed effects model, allowing for arbitrary correlation between the unobserved effect and the observed explanatory variables. The identification comes from the within firm changes in equity volatility and loan spreads. We report the results in the first two columns of Table 3. The results further confirm our findings that idiosyncratic volatility is positively priced and systematic volatility is negatively priced. The weak significance of systematic volatility is the result of short dimension along facilities within the borrower as each firm borrows on average 2.7 facilities in our sample[11]. Likewise, to rule out the effect of unobserved bank characteristics on lending rates, we reorganize our sample into panel data in which b=bank and f=facility. We estimate a bank fixed effects model that eliminates the unobserved bank specific effects which are heterogenous across lenders but are constant over facilities of the same lender. We present basically the same results in columns 3 and 4. We have very statistically significant results as each bank lends on average 30 facilities in our sample.

Taken together, we find that loan spreads are positively related to idiosyncratic risk but negatively related to aggregate risk of the borrower. The underpricing of aggregate risk relative to idiosyncratic risk can be interpreted as evidence of bank systemic risk taking in syndicated loans. In the next section, we investigate the incentives for banks taking systemic

[11]We fail to have significant results once we use firm-bank fixed effects as each firm-bank pair has only 1.8 facilities which indicates loss of massive information in regressions.

risk.

4 Systemic risk-taking and public guarantees: Do nonbank lenders take systemic risk?

The "search for yield" argument that investors tend to buy riskier assets in order to reach higher returns is prevailing in the literature (Rajan, 2006; Becker and Ivashina, 2013; Iannotta and Pennacchi, 2012). However, this hypothesis cannot explain what we find in the syndicated loan pricing as banks tend to underprice systematically risky loans rather than charging a risk premium for bearing the aggregate risk. On the contrary, such lending rate discount for aggregate risk seems to be consistent with the prediction of regulatory arbitrage hypothesis that banks exploit regulatory subsidies from public guarantees. In particular, banks are protected by explicit or implicit public guarantees that regulators and government will support them in systemic crisis in forms of capital injection or liquidity support, whereas the losses from individual default of borrowers are borne by banks. Hence banks may be less worried about aggregate risk. On the contrary, nonbank lender peers which are not protected by any public guarantee should have no incentive to take systemic risk[12]. In this part, applying the pricing model to the loans originated by both bank and nonbank investors, we use the presence (or absence) of public guarantee to identify the impact of guarantees on risk-taking.

The loans originated by nonbank lenders are much fewer than the bank loans in the U.S. syndicated loan market. We collect 1788 loans granted by finance companies, corporations, mutual funds and etc. We compare the loan pricing patterns by nonbank lenders and bank lenders in Table 4. As the accounting information for nonbank lenders is not as accessible as banks, we only control for borrower, loan specific variables and year dummies. We find systemic risk and idiosyncratic risks are priced similarly by nonbank lenders in columns 1 and 3. In particular, the estimated coefficient for systematic risk is slightly greater that the coefficient of idiosyncratic risk, in line with the prediction of the standard asset pricing theory. In other words, the aggregate risk has been priced in the absence of public guarantee by the nonbank lenders. For comparison, we report the regression for bank lenders in columns 2 and 4, in which our main results that systematic risk is underpriced relative to idiosyncratic risk still hold. Overall, the absence of the underpricing of systematic risk in the nonbank lender

[12] For descriptions of the role of nonbank lenders in the syndicated loan market, see Ivashina and Sun (2011).

cohort suggests that the systemic risk taking of banks is driven by the public guarantee.

5 Too-big-to-fail or too-many-to-fail?

What kind of public guarantee matters for systemic risk-taking here in the syndicated loan market? The traditional "too-big-to-fail" theory asserts that certain banks are so large that their failures may incur huge costs to the economy and that hence they are very likely to get support from regulators and governments in systemic crisis. Therefore, big banks are likely to take risk to exploit the safety net, therefore underprice aggregate risk, according to the "too-big-to-fail" story. But can the systemic risk-taking we observed in the U.S. syndicated loan market be explained by the "too-big-to-fail" guarantee? To identify the impact of bank size on risk pricing, we construct a dummy variable *SmallBK* that equals one if the bank size is smaller than the median value and zero otherwise. We then interact the small bank dummy with borrowers' equity volatilities. Overall, we run the following regression:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 SysVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times SmallBK_{b,t-1} \\ &+ \alpha_4 SysVol_{i,t-1} \times SmallBK_{b,t-1} + \alpha_5 SmallBK_{b,t-1} \\ &+ \sum_j \gamma_j Firm_{i,t-1} + \sum_k \theta_k Loan_{f,t} + \sum_n \psi_n Bank_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t} \end{aligned} \tag{4}$$

We present the results in Table 5. In column 1, we find banks generally charge a higher spread for idiosyncratic risk. The coefficient for systematic risk and the interaction between idiosyncratic risk and *Small BK* are negative and insignificant. However, the interaction term between aggregate risk and *Small BK* is negative and significant, suggesting that small banks underprice aggregate risk relative to big banks. In the end, the coefficient of *Small BK* is positive and significant, indicating that generally small banks charge higher lending rates. Overall we find small banks underprice aggregate risk to idiosyncratic risk more relative to big banks do, indicating that small banks are more aggressive in taking systemic risk. For sensitivity analysis, we split our full sample into loans originated by small banks and big banks and report the results in columns 2 and 3. The exercises based on Fama French equity volatilities in columns 4 to 6 yield similar results. Taken together, we find small banks tend to underprice systematic risk, which is different from the prediction of "too-big-to-fail" theory.

The fact that small banks are more aggressive in underpricing aggregate risk and therefore taking systemic risk is in line with the prediction of "too-many-to-fail" guarantee. Acharya and Yorulmazer (2007) model the "too-many-to-fail" problem that a bank regulator finds it ex post optimal to bail out failed banks when the number of failures is large, whereas the probability of the collective bailout is low when the number of bank failures is small, as failed banks can be acquired by surviving banks. The ex post optimal bailout exists in the circumstance that the costs of injecting funds are smaller than the misallocation cost of liquidating bank assets to outside investors in case of systemic banking crisis. Therefore, the bailout expectation creates incentives for banks to herd ex ante in order to maximize the likelihood of failing together and therefore collective bailout. In particular, Acharya and Yorulmazer show that small banks have stronger incentives to take systemic risk under the "too-many-to-fail" guarantee. The rationale is that the bailout subsidy increases for small banks when big banks have also failed while it does not increase for big banks when small banks have also failed. Brown and Dinc (2009) document evidence of the "too-many-to-fail" effect that a government is less likely to close a failing bank if other banks in that country are weak.

One caveat of our above test is that our results may be driven by the fact that small banks with small loan portfolios cannot achieve perfect diversification and hence charge higher spreads on idiosyncratic risk relative to aggregate risk. As loan portfolios are not perfectly observable, we turn to directly test the "too-many-to-fail" argument by assessing the impact of interbank correlation on loan pricing, which is not confounded by the bank level of portfolio diversification. The idea is that lowly correlated banks have stronger incentives to increase interbank correlation and therefore take systemic risk in order to maximize the likelihood of failing together with systemically important banks. Therefore "too-many-to-fail" argument predicts that small banks underprice aggregate risk relative to idiosyncratic risk more compared to more correlated banks. To measure the interbank correlation, we first calculate the correlation of bank daily excess return with the S&P 500 banking sector index using the data one year prior to the quarter of loan origination. We construct a dummy variable $LowCorrBK$ that equals one if the bank correlation is smaller than the median value and zero otherwise. We then interact the bank correlation with borrowers' equity volatilities.

We run the following regression:

$$\begin{aligned} LoanSpread_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 SysVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times LowCorrBK_{b,t-1} \\ &+ \alpha_4 SysVol_{i,t-1} \times LowCorrBK_{b,t-1} + \alpha_5 LowCorrBK_{b,t-1} \\ &+ \sum_j \gamma_j Firm_{i,t-1} + \sum_k \theta_k Loan_{f,t} + \sum_n \psi_n Bank_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t} \end{aligned} \tag{5}$$

We report the results based on CAPM equity volatilities in column 1 in Table 6. We find the idiosyncratic volatility is positively related to loan spreads, suggesting that banks charge a risk premium for bearing the firm-specific default risk. On the contrary, the coefficient of aggregate risk is negative but insignificant. The interaction term between idiosyncratic volatility and low correlation dummy is positive and weakly significant. However, the interaction between systematic volatility and low correlation dummy is negative and significant, suggesting that lowly correlated banks charge lower lending rates on aggregate risk relative to more correlated banks. Taken together, we find lowly correlated banks underprice aggregate risk more relative to more correlated banks.

To relax the restrictions of identical coefficients of the firm, loan and bank specific covariates for correlated and lowly correlated banks in the baseline regression, we divide our sample into two corresponding subsamples. We report the results of sample split in the columns 2 and 3. We find that systematic risk is negatively and significantly priced by lowly correlated banks whereas insignificantly priced by more correlated banks. This indicates lowly correlated banks have stronger incentives to take systematic risk of borrowers and therefore increase systemic risk. We do the same exercise using Fama French equity volatilities and have similar results in columns 4 to 6. Overall, we find evidence that lowly correlated banks have stronger incentive to underprice aggregate risk and therefore take systemic risk, consistent with the "too-many-to-fail" story.

6 Do lowly correlated banks lend more to systematically risky borrowers?

Having shown that lowly correlated banks underprice systematic risk, we examine whether they lend more to systematically risky borrowers. A large stake in the syndicated loans granted to systematically risky borrowers is another indicator of systemic risk-taking. We adopt two measures of lenders stake in syndicated lending: Share Exposure, which is the share of the facility held by the bank, and Dollar Exposure, which is the log of facility amount retained by the bank. We estimate the following model:

$$\begin{aligned}Stake_{i,f,b,t} =& c + \alpha_1 IdioVol_{i,t-1} + \alpha_2 SysVol_{i,t-1} + \alpha_3 IdioVol_{i,t-1} \times LowCorrBK_{b,t-1} \\ & + \alpha_4 SysVol_{i,t-1} \times LowCorrBK_{b,t-1} + \alpha_5 LowCorrBK_{b,t-1} \\ & + \sum_j \gamma_j Firm_{i,t-1} + \sum_k \theta_k Loan_{f,t} + \sum_n \psi_n Bank_{b,t-1} + \sum_t \delta_t T + \epsilon_{i,f,b,t}\end{aligned} \tag{6}$$

We report the regression results that lowly correlated banks take a large share of the loan and a large loan size when lending to a systematically risky borrower in Table 7. We use the relative take measure, Share Exposure, as the dependent variable in the first two columns. We find banks generally hold a large share of the facility if the idiosyncratic risk of the borrower is high and systematic risk is low. However, lowly correlated banks take a large share when the borrower is systematically risky, in line with our prediction that lowly correlated banks have stronger incentives to invest in systematic risk and to increase asset correlation. In the last two columns we use the absolute stake measure, Dollar Exposure, as the dependent variable. We have similar results that lowly correlated banks take a large size of loans when the borrower is systematically risky. It is worth noting that the number of observations in the regression drops drastically since the information of loan share retained by the lead arranger is available for 47 % of our loan facilities. Overall, we conclude that lowly correlated banks not only charge a lower lending rate to the systematically risky borrowers, but also take larger stake in systematically risky loans.

7 Conclusion

This paper documents evidence of bank systemic risk taking from loan pricing data. We find loan spreads are positively related to borrowers' idiosyncratic risk but negatively related to systematic risk. The lending rate discount for systematic exposure reveals banks' preference for increased correlation and systemic risk. We relate this collective moral hazard to the "too-many-to-fail" guarantee in bank regulation. We show that no evidence of such systemic risk taking could be found in the loans originated by nonbank lenders in absence of bailout expectation. In line with the "too-many-to-fail" theory in Acharya and Yorulmazer (2007), we find lowly correlated and small banks are more aggressive in systemic risk taking as they underprice systematic risk of the borrower more relative to more correlated and big banks. This finding also suggests that our results are not driven by "too-big-to-fail" guarantee.

Our results have direct policy implications for macro prudential regulations. First, the fact that banks take advantage of the financial safety net and pass through regulatory subsidies to borrowers in the form of inappropriate pricing of risk may threat the stability of the whole banking sector. The prudential regulation should be designed to force banks to internalize the social costs incurred in the systemic crisis so that the incentive for systemic risk-taking is dampened. In particular, bank regulation should operate at the collective level to pay more attention to systemic risk on top of individual risk to cope with the collective moral hazard of systemic risk-taking (Acharya, 2009). Second, much attention has been paid to systemically important financial institutions (SIFI) which contribute substantially to systemic risk. However, in this paper we show that small and lowly correlated banks which are aggressive in taking systemic risk need attention for regulation as well.

Table 1: Summary Statistics

	No.	Mean	Std. Dev	1th	Median	99th
AllinDrawn	11278	208.67	124.53	20	200	578.08
Borrower Equity Volatility						
TotalVol	11278	0.59	0.35	0.17	0.5	1.71
MarketVol	11278	0.16	0.07	0.08	0.13	0.4
$IdioVol^{CAPM}$	11278	0.56	0.35	0.16	0.48	1.7
$IdioVol^{FF}$	11278	0.56	0.35	0.15	0.47	1.69
$SysVol^{CAPM}$	11278	0.12	0.11	-0.05	0.1	0.53
$SysVol^{FF}$	11276	0.16	0.11	0.02	0.13	0.59
$Beta^{CAPM}$	11278	0.76	0.59	-0.43	0.7	2.47
$Beta\_mkt^{FF}$	11278	0.97	0.66	-0.63	0.95	2.8
$Beta\_smb^{FF}$	11278	0.84	0.83	-1.03	0.78	3.22
$Beta\_hml^{FF}$	11278	0.29	1.05	-2.61	0.3	3.13
Firm controls						
Sales	11278	5.6	1.77	1.62	5.55	9.86
Leverage	11278	28.07	21.6	0	26.32	93.38
Z score	11278	4.07	7.44	-2.45	3.06	21.42
Profit Margin	11278	-20.75	1049.91	-156.99	3.19	27.55
NWC	11278	21.19	21.74	-28.73	19.7	74.26
Tangibles	11278	69.41	39.78	5.77	66.38	175.83
MRTBOOK	11278	1.82	1.48	0.67	1.45	6.81
Loan controls						
Facility Size	11278	3.79	1.78	-0.69	3.91	7.38
Share Exposure	5757	56.46	37.35	4.5	50	100
Dollar Exposure	5746	2.64	1.33	-0.92	2.80	5.52
Maturity	11278	43.02	25.21	4	37	102
No. Lenders	11278	6.01	7.71	1	3	36
No. Facilities	11278	1.77	0.99	1	1	5
Revolver	11278	0.73	0.44	0	1	1
Term Loan	11278	0.24	0.43	0	0	1
Senior	11278	1	0.04	1	1	1
Secured	11278	0.75	0.43	0	1	1
Bank controls						
Size BK	11278	18.15	1.92	13.13	18.21	21.27
Capital BK	11278	7.58	2.49	3.53	7.23	14.89
NPL BK	11278	0.95	1.1	0	0.56	4.91
Z Score BK	11278	3.17	0.53	0.74	3.25	4.03
ROA BK	11278	0.95	0.65	-1.69	1.04	2.24
Liquidity BK	11278	18.77	8.9	3.92	18.15	46.14
Loan Growth BK	11278	22.37	56.73	-35.89	9.19	199.01
Cost of Funds BK	11278	3.42	1.8	0.52	3.31	10.52
InterbankCorr	9251	0.73	0.16	0.11	0.78	0.93

Table 2: Baseline

	(1) CAPM	(2) Fama French	(3) CAPM
$IdioVol^{CAPM}$	99.26***		
	(5.42)		
$SysVol^{CAPM}$	-41.46***		-67.02***
	(13.42)		(13.94)
$IdioVol^{FF}$		102.87***	
		(5.75)	
$SysVol^{FF}$		-39.33***	
		(13.18)	
$TotalVol$			99.78***
			(5.51)
Sales	-5.95***	-6.01***	-6.00***
	(1.02)	(1.02)	(1.02)
Leverage	0.62***	0.61***	0.62***
	(0.07)	(0.07)	(0.07)
Z score	-0.48	-0.48	-0.48
	(0.48)	(0.48)	(0.48)
Profit Margin	-0.26***	-0.26***	-0.26***
	(0.06)	(0.06)	(0.06)
NWC	-0.24***	-0.23***	-0.24***
	(0.07)	(0.07)	(0.07)
Tangibles	-0.11***	-0.11***	-0.11***
	(0.03)	(0.03)	(0.03)
MRTBOOK	-0.04***	-0.04***	-0.04***
	(0.01)	(0.01)	(0.01)
Facility Size	-8.98***	-8.85***	-8.99***
	(1.08)	(1.08)	(1.08)
Maturity	-0.40***	-0.40***	-0.40***
	(0.05)	(0.05)	(0.05)
No. Lenders	-0.52***	-0.53***	-0.53***
	(0.17)	(0.17)	(0.17)
No. Facilities	11.97***	11.91***	12.02***
	(1.61)	(1.62)	(1.62)
Revolver	-39.67***	-39.39***	-39.65***
	(6.94)	(6.92)	(6.95)
Term Loan	-9.44	-9.20	-9.47
	(7.25)	(7.24)	(7.26)
Senior	-193.77***	-194.07***	-193.66***
	(44.49)	(44.38)	(44.40)
Secured	74.21***	74.30***	74.42***
	(2.45)	(2.45)	(2.45)
Size BK	-4.86***	-4.86***	-4.88***
	(0.94)	(0.94)	(0.94)
Capital BK	-2.47***	-2.45***	-2.47***
	(0.75)	(0.75)	(0.75)
NPL BK	4.11**	4.08**	4.13**
	(1.64)	(1.64)	(1.64)
ROA BK	1.82	1.87	1.77
	(2.27)	(2.27)	(2.27)
Z Score BK	-2.03	-1.99	-2.08
	(2.87)	(2.87)	(2.87)
Liquidity BK	-0.22	-0.22	-0.22
	(0.16)	(0.16)	(0.16)

Loan Growth BK	-0.07**	-0.07**	-0.07**
	(0.03)	(0.03)	(0.03)
Cost of Funds BK	-3.04**	-3.02**	-3.07**
	(1.23)	(1.22)	(1.23)
Constant	528.76***	530.93***	529.12***
	(49.62)	(49.51)	(49.54)
Year Dummies	Yes	Yes	Yes
Loan Purpose Dummies	Yes	Yes	Yes
Observations	11,278	11,276	11,278
R-squared	0.554	0.555	0.554

Table 3: Panel Regressions

The dependent variable is all-in-drawn spread. Standard errors are adjusted for clustering at the borrower level in the first two columns and at the bank level in the last two columns and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1) CAPM	(2) Fama French	(3) CAPM	(4) Fama French
$IdioVol^{CAPM}$	108.93***		99.16***	
	(8.79)		(7.20)	
$SysVol^{CAPM}$	-45.45**		-48.53***	
	(19.38)		(15.52)	
$IdioVol^{FF}$		111.41***		102.76***
		(9.11)		(6.54)
$SysVol^{FF}$		-35.02*		-42.88**
		(20.24)		(17.09)
Firm control	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes
Bank control	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No
Number of Firms	4,183	4,182	N.A.	N.A.
Bank FE	No	No	Yes	Yes
Number of Banks	N.A.	N.A.	381	381
Observations	11,278	11,276	11,278	11,276
R-squared	0.329	0.329	0.487	0.487

Table 4: Nonbank and Bank Lenders

The dependent variable is all-in-drawn spread. Standard errors are adjusted for clustering at the borrower level and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1) Nonbank	(2) Bank	(3) Nonbank	(4) Bank
$IdioVol^{CAPM}$	59.38***	100.04***		
	(11.58)	(5.39)		
$SysVol^{CAPM}$	76.00**	-34.47**		
	(38.59)	(13.58)		
$IdioVol^{FF}$			55.17***	103.52***
			(12.35)	(5.72)
$SysVol^{FF}$			65.36*	-34.84***
			(39.12)	(13.36)
Firm control	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	1,788	12,080	1,785	12,078
R-squared	0.348	0.536	0.348	0.536

Table 5: Bank size matters

The dependent variable is all-in-drawn spread. Standard errors are adjusted for clustering at the borrower level and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1) Full	(2) Small	(3) Big	(4) Full	(5) Small	(6) Big
$IdioVol^{CAPM}$	107.28***	85.75***	120.80***			
	(8.54)	(6.28)	(9.71)			
$SysVol^{CAPM}$	-14.71	-71.22***	-14.70			
	(18.42)	(17.64)	(19.84)			
$IdioVol^{CAPM} * smallBK$	-11.90					
	(9.01)					
$SysVol^{CAPM} * smallBK$	-55.97**					
	(22.31)					
$IdioVol^{FF}$				108.42***	92.67***	122.32***
				(9.04)	(6.73)	(10.17)
$SysVol^{FF}$				-10.51	-76.20***	-12.26
				(17.67)	(17.81)	(18.72)
$IdioVol^{FF} * smallBK$				-6.82		
				(9.57)		
$SysVol^{FF} * smallBK$				-61.31***		
				(22.23)		
$smallBK$	19.92***			19.98***		
	(5.28)			(5.30)		
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Bank control	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,278	5,579	5,699	11,276	5,578	5,698
R-squared	0.553	0.501	0.577	0.554	0.502	0.577

Table 6: Loan pricing depends on bank correlation

The dependent variable is all-in-drawn spread. Standard errors are adjusted for clustering at the borrower level and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1) Full	(2) Less Corr.	(3) More Corr.	(4) Full	(5) Less Corr.	(6) More Corr.
$IdioVol^{CAPM}$	93.38***	96.63***	106.75***			
	(7.72)	(8.13)	(8.82)			
$SysVol^{CAPM}$	-11.17	-63.03***	-16.76			
	(18.53)	(22.02)	(19.45)			
$IdioVol^{CAPM}$*LowCorrBK	17.22*					
	(8.92)					
$SysVol^{CAPM}$*LowCorrBK	-53.90**					
	(24.87)					
$IdioVol^{FF}$				94.80***	102.36***	109.54***
				(8.11)	(8.58)	(9.19)
$SysVol^{FF}$				-11.07	-67.51***	-19.51
				(17.67)	(21.62)	(18.46)
$IdioVol^{FF}$*LowCorrBK				21.42**		
				(9.46)		
$SysVol^{FF}$*LowCorrBK				-55.00**		
				(24.42)		
LowCorrBK	1.04			1.01		
	(5.31)			(5.28)		
Firm control	Yes	Yes	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes	Yes	Yes
Bank control	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,251	4,585	4,666	9,249	4,584	4,665
R-squared	0.565	0.583	0.561	0.566	0.584	0.562

Table 7: Share and Size of loans

The dependent variables are the share of facility held by the bank (Share Exposure) in the first two columns and the log of facility amount held by the bank (Dollar Exposure) in the last two columns, respectively. Standard errors are adjusted for clustering at the borrower level and reported in parentheses below coefficients. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

	(1) Share Exposure	(2) Share Exposure	(3) Dollar Exposure	(4) Dollar Exposure
$IdioVol^{CAPM}$	11.55***		-0.28***	
	(2.42)		(0.10)	
$SysVol^{CAPM}$	-19.18***		0.15	
	(6.04)		(0.22)	
$IdioVol^{CAPM}$*LowCorrBK	-1.86		-0.18	
	(2.61)		(0.11)	
$SysVol^{CAPM}$*LowCorrBK	20.74**		0.84**	
	(8.59)		(0.33)	
$IdioVol^{FF}$		12.46***		0.27***
		(2.57)		(0.05)
$SysVol^{FF}$		-15.45**		-0.38***
		(6.21)		(0.14)
$IdioVol^{FF}$*LowCorrBK		-3.43		-0.08
		(2.82)		(0.05)
$SysVol^{FF}$*LowCorrBK		21.93**		0.31*
		(9.33)		(0.16)
LowCorrBK	0.27	0.14	-0.01	0.01
	(1.89)	(1.86)	(0.08)	(0.04)
Firm control	Yes	Yes	Yes	Yes
Loan control	Yes	Yes	Yes	Yes
Bank control	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	4,455	4,454	4,447	4,446
R-squared	0.706	0.706	0.587	0.894

APPENDIX

Table 8: Variables and Sources

Variable	Definition and Calculation	Source
AllinDrawn	All-in-drawn spread is a spread over Libor.	Dealscan
Equity volatility of borrowers		
$IdioVol^{CAPM}$	Idiosyncratic volatility using one factor CAPM regressions. Defined as the standard deviation of the residual.	CRSP
$SysVol^{CAPM}$	Systematic volatility using one factor CAPM regressions. Defined as the product of beta and market volatility.	CRSP
$IdioVol^{FF}$	Idiosyncratic volatility from Fama French three factor model. Defined as the standard deviation of the residual.	CRSP and WRDS
$SysVol^{FF}$	Systematic volatility from Fama French three factor model. Defined as the total volatility that is attributable to Fama French factors and the factors cross-covariances.	CRSP and WRDS
$Beta^{CAPM}$	Equity beta estimated from the CAPM regression.	CRSP
$Beta\_mkt^{FF}$	Market beta estimated from the Fama French three factor regression.	CRSP and WRDS
$Beta\_smb^{FF}$	Size beta estimated from the Fama French three factor regression.	CRSP and WRDS
$Beta\_hml^{FF}$	Value beta estimated from the Fama French three factor regression.	CRSP and WRDS
$TotalVol$	Total equity volatility, defined as the standard deviation of daily excess return one year before the facility start date.	CRSP

Table 9: Variables and Sources: Continue

Variable	Definition and Calculation	Source
Firm level controls		
Sales	log of firm sales at close.	Dealscan
Leverage	Firm leverage defined as sum of long term and short term debts over total assets.	Compustat
Z score	Firm Z score $1.2 \times (act - lct)/at + 1.4 \times (re/at) + 3.3 \times (oiadp/at) + 0.6 \times (prcc \times csho/lt) + 0.999 \times (sale/at)$	Compustat
Profit Margin	Profit margin over sales.	Compustat
NWC	Net working capital over total assets.	Compustat
Tangibles	Tangible assets over total assets.	Compustat
MRTBOOK	Market to book ratio.	Compustat
Loan level controls		
Facility Size	Log of facility amount, adjusted for currency and unit	Dealscan
Share Exposure	The share of loans retained by the lead arranger in the facility.	Dealscan
Dollar Exposure	Log of the amount of loans retained by the lead arranger in the facility.	Dealscan
Maturity	Maturity of the facility in terms of months	Dealscan
No. Lenders	Number of lenders in a tranche of a syndicated loan deal	Dealscan
No. Facilities	Number of facilities (tranches) in a syndicated loan deal	Dealscan
Revolver	dummy for lines of credit.	Dealscan
Term Loan	dummy for term loans.	Dealscan
Senior	dummy for senior loans.	Dealscan
Secured	dummy for loans with collateral.	Dealscan

Table 10: Variables and Sources: Continue

Variable	Definition and Calculation	Source
Bank level controls		
Size BK	Log of bank total assets.	Call reports and FR-Y9C
Small BK	Dummy for small banks.	Call reports and FR-Y9C
Capital BK	Bank equity over total assets.	Call reports and FR-Y9C
NPL BK	Nonperforming loans over gross loans.	Call reports and FR-Y9C
Z Score BK	Bank Z score, defined as sum of equity asset ratio and ROA divided by standard deviation of ROA. We use 8-quarter rolling window when calculating the standard deviation of ROA. We take log transformation as in Laeven and Levine (2009).	Call reports and FR-Y9C
ROA BK	Return on assets.	Call reports and FR-Y9C
Liquidity BK	Liquid assets over total assets.	Call reports and FR-Y9C
Loan Growth BK	Growth rates of gross loans.	Call reports and FR-Y9C
Cost of Funds BK	Cost of funds, defined as total interest expenses over total liabilities.	Call reports and FR-Y9C
InterbankCorr	Interbank correlation, defined as the correlation between bank stock return and S&P 500 bank sector index.	CRSP and Datastream
LowCorrBK	Dummy for less correlated banks of which interbank correlation is below median value.	CRSP and Datastream

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